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Modeling and optimization of a chiller plant

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ABSTRACT

A data-driven approach is utilized to model a chiller plant that has four chillers, four cooling towers, and two chilled water storage tanks. The chillers have varying energy efficiency. Since the chiller plant model derived from data-driven approach is nonlinear and non-convex, it is not practical to solve it by using the traditional gradient-based optimization algorithm. A two-level intelligent algorithm is developed to solve the model aiming at minimizing the total cost of the chilled water plant. The proposed algorithm can effectively search the optimum under the non-convex and nonlinear situation. A simulation case is conducted and the corresponding results are discussed.

1. Introduction

A chiller plant normally consists of chillers, cooling towers, pumps and chilled water storage tanks. It is frequently used to air conditioning large office buildings or campuses with multiple buildings [1]. More than 40% of the total electricity in a building is consumed by the chiller system. Thus effective energy management of chiller plants is becoming important to save energy consumption and reduce environmental impact [2].

Managing a chiller plant is a complex and challenging task. Many work and research have been reported in literature for optimizing one of the components in a chiller plant [3–8]. For example, Chan and Yu developed a chiller model based on a simulation program [9]. Optimum set point of condensing water temperature for chillers was found and controlled to reduce fluctuation in chiller efficiency in different operating conditions. Fisenko et al. [10] presented a mathematical model of a control system of the mechanical draft cooling tower. The control system was able to optimize the performance of the cooling tower under changing atmospheric conditions. Mathematical models associating with cooling loads and energy consumption were established by Lu et al. [11] to calculate optimal set points based on sensor information. Operating the chilled water system at optimized chilled water supply temperature, chilled water pump head and other set points was found with significant reduction in energy consumption.

For the chiller plant having multiple chillers, not all chillers are running at the same time. Optimal sequencing chillers can improve energy efficiency of the chiller plant [12–14]. Chang [15–17] used different methods to search optimal chiller sequence, such as dynamic programming, neural networks, branch and bound method. The results indicated that energy savings can be obtained simply by changing chiller sequences. A robust chiller sequencing control strategy was proposed by Huang et al. [18] for central chiller plants. Data fusion scheme and fault detection and diagnosis scheme were developed to improve the reliability. The control strategy was validated by the dynamic simulation of the central chiller plant.

For those improvements based on optimization of single component of a chiller plant, the interactions among components are neglected. In fact, a chiller plant is a system in which components affect and are affected by the operation of the plant. In addition to equipment themselves, many other factors influence chiller plant's energy consumption. Such factors include weather, number and type of operating time, building use and cooling loads [19]. It is critical to consider the interactions and factors when managing a chiller plant to improve the energy efficiency.

In this paper, a chiller plant that has four chillers, four cooling towers of varying energy efficiency is considered. The plant also has two chilled water storage tanks that can be used to store the chilled

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water under the following two cases: first, the plant can produce more chilled water when the electricity price is low; second, the plant can produce more chilled water when the demand is not high and this excessive chilled water can be used when the demand is more than it can produce. A data-driven approach [20–22] is employed to model this plant based on the dataset collected from the historical operation of this plant. Since the model derived from data-driven approach is nonlinear and non-convex, the traditional gradient-based optimization algorithm cannot solve it efficiently. Thus, a strengthened genetic algorithm is designed to solve the model aiming at minimizing the total cost of the chilled water plant. A simulation case is conducted in the last section and the corresponding results are discussed.

2. Chiller plant modeling

2.1. Chiller plant description

Fig. 1 illustrates the schematic diagram of a typical chiller plant. The chiller plant is usually consisted of chillers, cooling towers, condensing water pumps, chilled water distribution pumps, chilled water storage tanks, and distribution pipes. The chillers in the plant can be connected in series or in parallel. The components that consume energy in the chiller plant include chiller compressors, cooling tower fans, condensing water pumps, and chilled water distribution pumps. A chiller plant that includes four chillers and four cooling towers connected in parallel is considered in this research. In addition, the plant has two chilled water storage tanks that can store excess chilled water when electricity price or demand is low. The stored chilled water can be used when electricity price or demand is high. By using the chilled water storage tanks, the cost of the plant can be saved. Fig. 2 shows a fluctuated hourly electricity price in a typical day. Thus an operation schedule of the chiller plant could be arranged over a demand period to minimize the total cost. Fig. 3 shows a chilled water demand for one typical day. To make the system simple, energy consumption of the pumps is not considered since it only accounts for a small part of the total energy consumption of the entire system. Assume that the energy consumed by unit i (a chiller and a cooling tower) at time t is u_{it}. Also, the electricity price at time t can be expressed as p_t. A decision variable x_{it} is introduced to turn on or turn off chiller i at time t for the following reason: The four chillers have different energy efficiency. Therefore it is necessary to decide which chiller should be used when the plant does not need to turn on all chillers. Thus, the total cost of the plant over one period (T) can be expressed as Eq. (1):

$$P_{\text{total}} = \sum_{t=0}^{T}\left(p_t \sum_{i=1}^{N} u_{it} \cdot x_{it}\right) \tag{1}$$

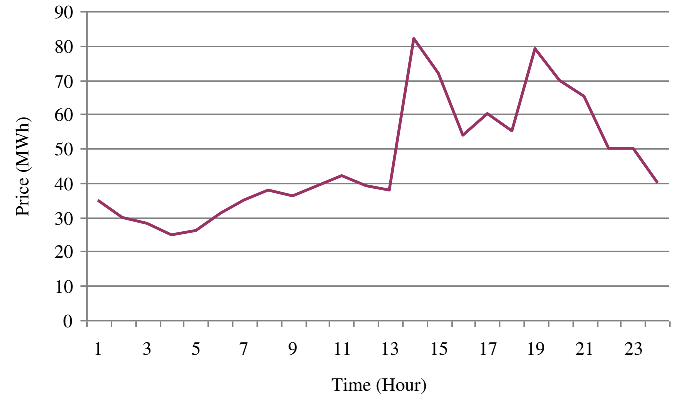

Fig. 2. The fluctuated hourly electricity price in a typical day.

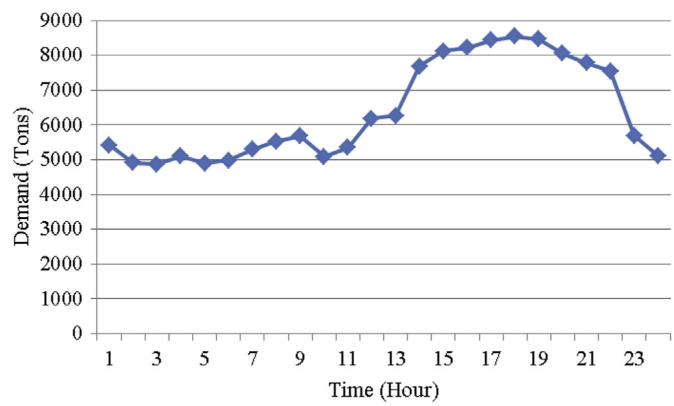

Fig. 3. The demand of cooling load in a typical day.

where P_{total} is the total cost of the plant, N is the number of the chillers.

The goal of this research is to minimize the total cost of the chiller plant. To achieve this goal, a schedule over a demand period to control the chillers should be made first and then two controllable variables of each chiller should be set at each time set p. The two controllable variables are chilled water flow (q_{it}) and the temperature difference of the condensing water (Δt_{it}). Thus, it is necessary to model the energy consumption for each unit. A data-driven approach is employed to build the model and the corresponding conceptual data-driven expression is presented in Eq. (2):

$$u_{it} = f_i(q_{it}, \Delta t_{it}, h_{t-1}) \tag{2}$$

Where h_{t-1} represents the enthalpy of ambient air at time step $t-1$.

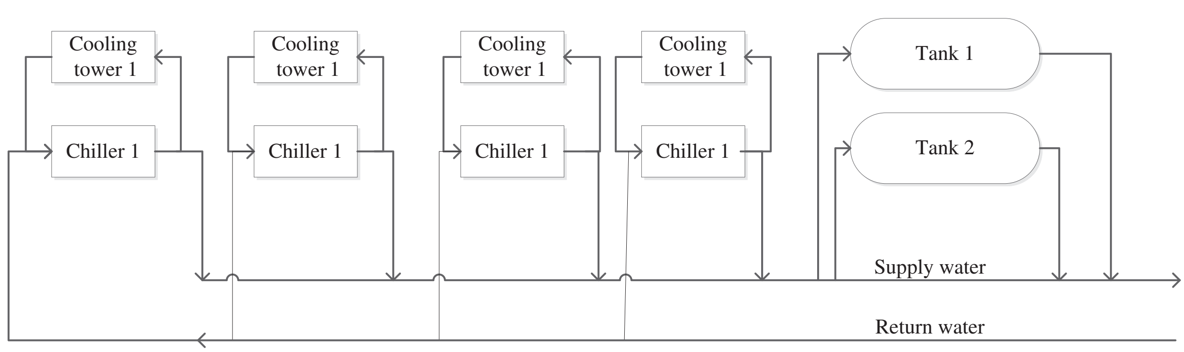

Fig. 1. Schematic diagram of a typical chiller plant.

As the decision variable is binary and the data-driven model is nonlinear, it is difficult to solve it with the traditional gradient-based algorithms. In this research, a two-level intelligent algorithm is designed to solve the non-convex and nonlinear model. A case study is conducted to validate the effectiveness of the proposed approach and the corresponding computational results are analyzed in the last section.

2.2. Data description

The chiller plant studied in this paper is operated by the University of Iowa Facilities Management. The plant has nine pairs of chillers and cooling towers. One pair of the chiller and cooling tower can compose one unit to produce chilled water. Four units with different nominal capacity from the plant are used for the research in this paper. Table 1 lists the nominal capacity for the four chillers produced by York OM. Since the four chillers have different lifetime, their performance efficiency have different characteristics. Although the performance curves were provided by the manufacturer, they are not able to provide exact estimation of the energy consumption of chillers. To obtain realistic performance efficiency, historical data is used to establish the relationship between the energy consumption and the produced chilled water, the temperature difference of the condensing water, and the enthalpy of ambient air. The historical data used in this research is from June 1 2011 to August 31 2011. In total, thirteen parameters listed in Table 2 were collected at 1-h increments. The processed data is listed in Table 3.

2.3. Data preprocessing

In a chiller plant, the temperature difference of the water through condensers has obvious cause and effect to energy consumption. Therefore, it is necessary to get the temperature difference of the condensing water by using condenser leaving water temperature deducting condenser entering water temperature. From the discussion of the above section, the energy consumption of the pumps is neglected in order to make the research simple. Thus, the objective of the model can be obtained from the summation of the power of the compressor and the cooling tower fan.

Table 1
Nominal capacity of the four chillers.

Chiller No.	Nominal capacity
1	3000 tons
2	3000 tons
3	2577 tons
4	2577 tons

Table 2
Data parameters from the chiller plant.

No.	Parameter name	Description
1	chw_tons_1	Cooling produced by chiller 1
2	chw_tons_2	Cooling produced by chiller 2
3	chw_tons_3	Cooling produced by chiller 3
4	chw_tons_4	Cooling produced by chiller 4
5	chr_kw_1	Power of chiller 1
6	chr_kw_2	Power of chiller 2
7	chr_kw_3	Power of chiller 3
8	chr_kw_4	Power of chiller 4
9	temp_diff_1	Temperature difference of condensing water of chiller 1
10	temp_diff_2	Temperature difference of condensing water of chiller 2
11	temp_diff_3	Temperature difference of condensing water of chiller 3
12	temp_diff_4	Temperature difference of condensing water of chiller 4
13	enthalpy	Enthalpy of ambient air of this research

Table 3
Description of data sets.

Data set	Dataset type	Number of instances
1	Unit 1	1810
2	Unit 2	1992
3	Unit 3	537
4	Unit 4	406

The above process is applicable for units 1, 2, 3, and 4. Eventually, the parameters used to build the power models of the four chillers are listed in Table 4.

2.4. Model construction

To build the prediction models in Eq. (2), a one-output-unit MLP (multi-layer perceptron) is applied [23]. The BFGS (broyden–-fletcher–goldfarb–shanno) method is used to train a network representing the prediction model. The data sets listed in Table 3 is used for training, testing, and validation of the data-driven models in Eq. (2). Based on Eq. (2), the derived data-driven model can be extended to a dynamic model by adding time dimension, shown in Eq. (3).

$$u_{it} = f_i(q_{it}, \Delta t_{it}, h) \quad (i = 1, 2, 3, 4; \;\; t = 0, 1, \dots, T) \tag{3}$$

From Eq. (3), the total energy consumption of the plant can be stated as Eq. (4):

$$P_{\text{total}} = \sum_{t=0}^{T} \left(p_t \sum_{i=1}^{N} f_i(q_{it}, \Delta t_{it}, h) \cdot x_{it} \right) \tag{4}$$

2.5. Model performance

To evaluate performance of the prediction models built by the MLP algorithm, four metrics are used: the MAE (mean absolute error) (Eq. (6)), the MAPE (mean absolute percentage error) (Eq. (8)), the Std_AE (standard deviation of absolute error) (Eq. (9)), and the Std_APE (standard deviation of absolute percentage error) (Eq. (10)) [24]. In Eq. (5), AE represents the absolute error of a single item. While in Eq. (7), APE represents the absolute percentage error of a single item.

$$\text{AE} = |\tilde{y} - y| \tag{5}$$

$$\text{MAE} = \frac{\sum_{i=1}^{n} \text{AE}_i}{N} \tag{6}$$

Table 4
Parameters selected for building energy consumption model of units 1–4.

Input	Parameter name
q_1	chw_tons_1
Δt_1	temp_diff_1
q_1	chw_tons_2
Δt_1	temp_diff_2
q_1	chw_tons_3
Δt_1	temp_diff_3
q_1	chw_tons_4
Δt_1	temp_diff_4
h	enthalpy

$$\mathrm{APE} = \left|\frac{\tilde{y} - y}{y}\right| \tag{7}$$

$$\mathrm{MAPE} = \frac{\sum_{i=1}^{n} \mathrm{APE}_i}{N} \tag{8}$$

$$\mathrm{Std\_AE} = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{AE}_i - \mathrm{MAE})^2}{N - 1}} \tag{9}$$

$$\mathrm{Std\_APE} = \sqrt{\frac{\sum_{i=1}^{n} (\mathrm{APE}_i - \mathrm{MAPE})^2}{N - 1}} \tag{10}$$

where $\tilde{y}$ is the predicted value, y is the actual observed value, and N is the number of data instances used for training, test, or validation.

3. Optimization model

3.1. Model formulation

To optimize the energy consumption of the chiller plant system, the function in Eq. (4) is considered as its objective function. In order to control the turning on or off of the chillers, Eq. (4) should be interpreted as:

Ifx_i=1, chiller i is on. Ifx_i=0, chiller i is off. Besides the binary variable applied to the chillers, two continuous variables are introduced: the first one determines the cooling u_{it} for chiller i at time increment t and the second one Δt_{it} determines the temperature difference of condensing water for chiller i at time t.

In order to make the model applicable in reality, the following constraints of the optimization model should be established:

- The cooling for each chiller cannot exceed the corresponding chiller's nominal capacity (Q_i);
- In order to operate the chiller economically, once the chiller is turned on, the cooling should larger than a fraction (γQ_i) of the nominal capacity of the corresponding chiller;
- The temperature difference of condensing water should be in a pre-set range[Δt_{min} , Δt_{max}];
- The cooling produced by the four chillers at time t plus the cooling stored in the tanks should be larger than the cooling load demand at time t (D_t);
- The cooling produced by the four chillers at time t plus the cooling stored in the tanks should not exceed the capacity of the tanks (C) and the cooling load at time t (D_t). The cooling storage in the tanks at time t denoted as (S_t)

The optimization model is formulated in Eq. (11).

$$\begin{array}{c}
\min \ P_{total} \\
\text{subject to :} \\
\mathrm{P_{total}} = \sum_{t=0}^{T} p_t \sum_{i=1}^{N} u_{it} \cdot x_{it} \\
\mathrm{u_{it}} = f_i(q_{it}, \Delta t_{it}, h) \\
\gamma \mathrm{Q_i} \le q_{it} \le Q_i \\
\Delta t_{\min} \le \Delta t_{it} \le \Delta t_{\max} \\
\mathrm{S_{t-1}} + \sum_{\mathrm{i}=1}^{\mathrm{N}} x_{it} u_{it} \ge D_t \\
S_{t-1} + \sum_{\mathrm{i}=1}^{\mathrm{N}} x_{it} u_{it} - D_t \le C \\
S_0 = S_T = 0 \\
\mathrm{x_{it}} \in \{0, 1\}
\end{array} \tag{11}$$

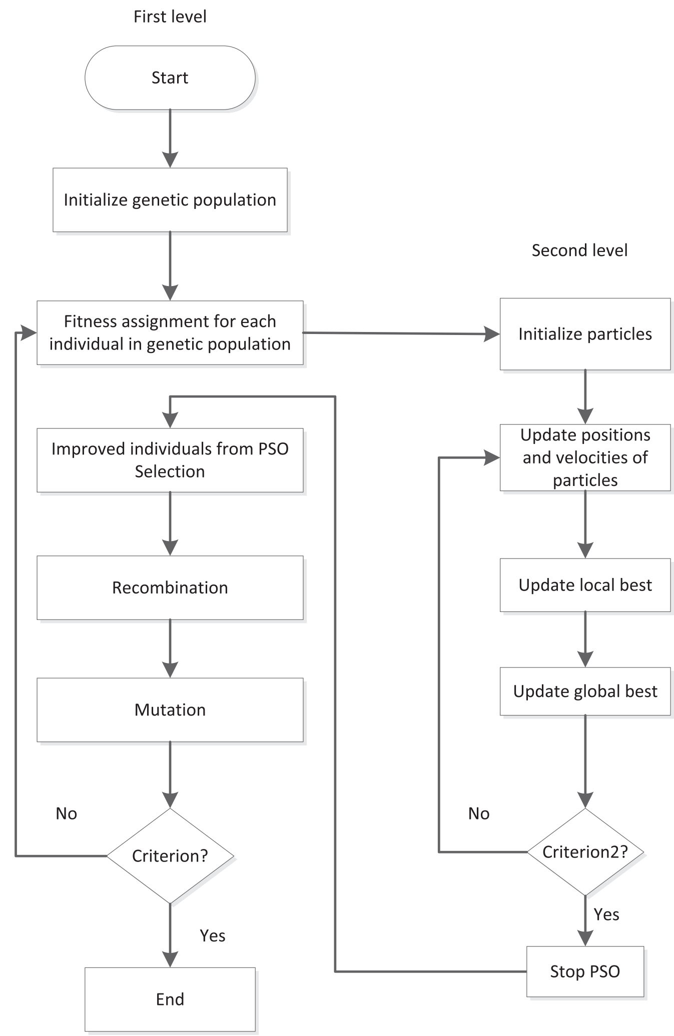

Fig. 4. . the flow chart of the two-level intelligent algorithm.

3.2. Two-level intelligent optimization algorithm

The optimization model Eq. (11) is non-convex, mixed-integer, and nonlinear. Therefore it is not suitable to be solved with traditional gradient-based optimization algorithms, e.g., the deepest descent algorithm. Considering this issue, a two-level intelligent algorithm is proposed in this research. The proposed algorithm includes, a genetic algorithm as the first level to control of the binary variable controlling the chillers, and at a second level a PSO

Table 5
Performance of the models predicting the energy consumption of the four units.

Objective	Data Set	MAE	MAPE	Std_AE	Std_MAPE
Unit 1	Training	30.18	1.77%	25.17	1.49%
	Validation	29.84	1.74%	24.73	1.46%
	Test	31.41	1.84%	25.79	1.53%
Unit 2	Training	25.01	1.49%	22.42	1.38%
	Validation	24.82	1.48%	24.17	1.50%
	Test	23.51	1.39%	21.54	1.29%
Unit 3	Training	52.15	2.92%	60.78	3.74%
	Validation	76.01	4.30%	79.59	4.82%
	Test	62.12	3.45%	74.25	4.43%
Unit 4	Training	23.29	2.33%	22.30	2.39%
	Validation	22.07	2.31%	29.73	3.27%
	Test	20.90	2.15%	18.99	2.29%

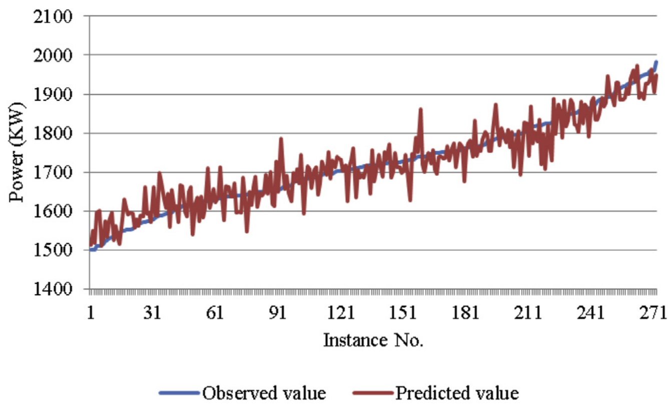

Fig. 5. Observed and predicted values of the energy consumption of unit 1.

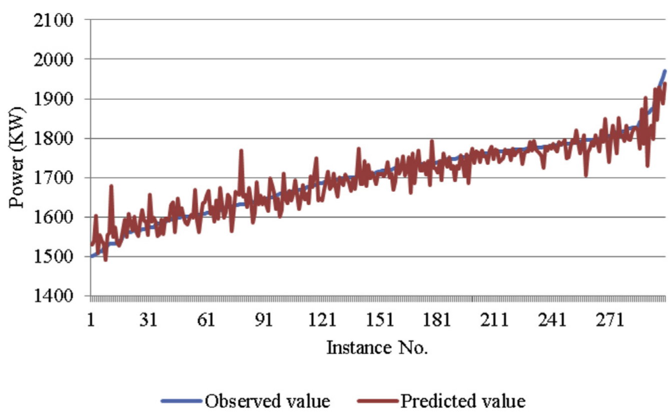

Fig. 6. Observed and predicted values of the energy consumption of unit 2.

(particle swarm optimization) algorithm is adopted for determining the two continuous variables (the entering water temperature of condensers and the cooling produced by chillers). The genetic algorithm [25] performs well for discrete variables, while the particle swarm optimization performs well for the continuous variables. The mechanism of the proposed algorithm can be stated as follows. The genetic algorithm firstly initializes the population and assigns the fitness for each individual. Then the PSO algorithm is applied to improve the fitness of each individual by searching the space of the two continuous variables. The improved individuals

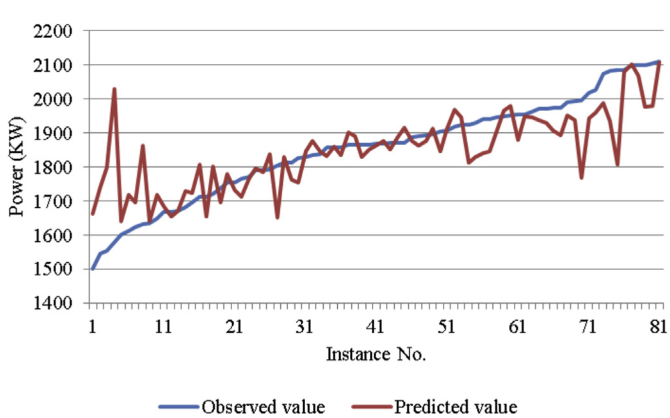

Fig. 7. Observed and predicted values of the energy consumption of unit 3.

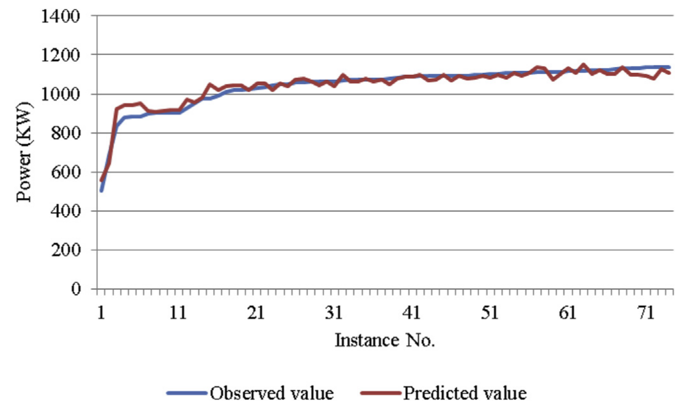

Fig. 8. Observed and predicted values of the energy consumption of unit 4.

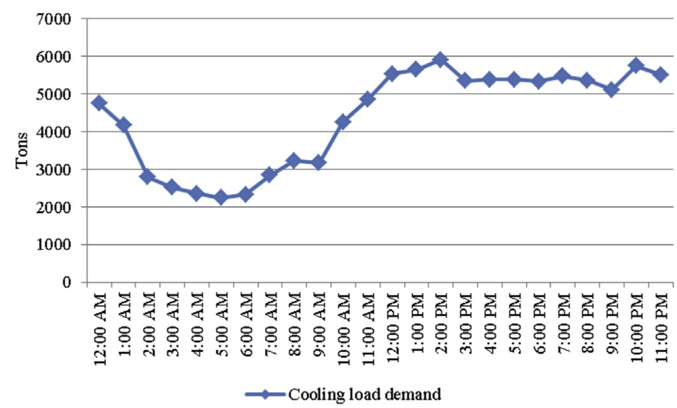

Fig. 9. The cooling load demand on June 1, 2011.

are sent back to the process of the genetic algorithm for the next steps.

Two observations made concerning the two levels:

Observation 1: If a binary variable at the first level is zero, no matter what the value of the continuous variables is at the second level, the contribution to the objective function is not affected.

Observation 2: If a binary variable in the first level is one, the continuous variables at the second level contribute to the objective function value.

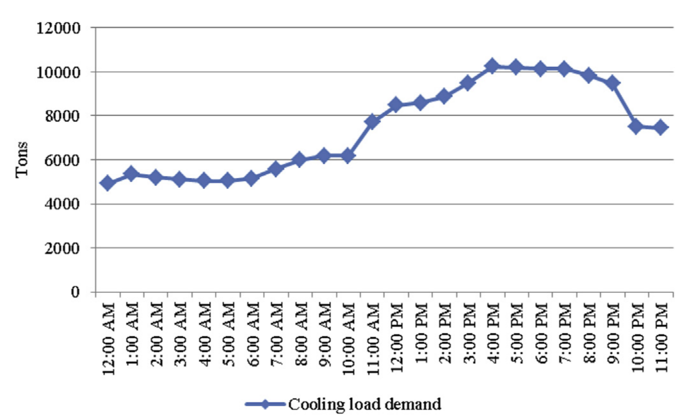

Fig. 10. The cooling load demand on July 16, 2011.

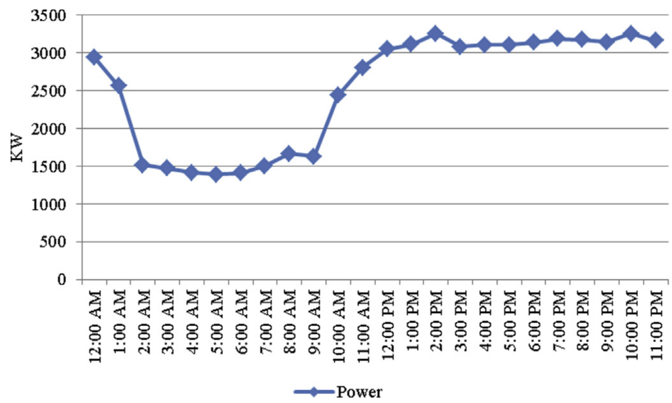

Fig. 11. The total energy consumption for the chiller plant on June 1, 2011.

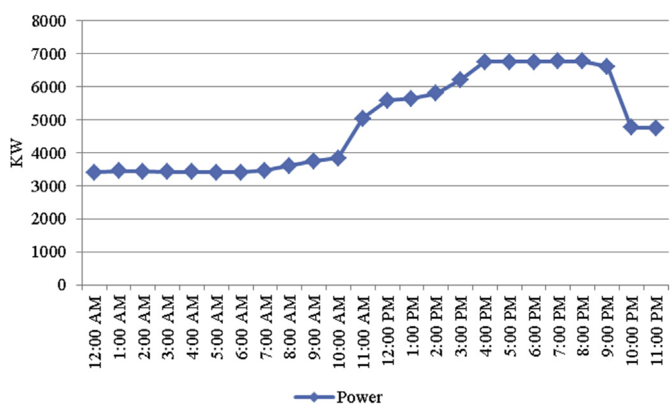

Fig. 12. The total energy consumption for the chiller plant on July 16, 2011.

Fig. 4 illustrates the steps of the two-level intelligent algorithm listed next.

Algorithm 1. (first level)

Set population size (pop), selection rate (r_s), recombination rate (r_c), and mutation rate (r_m) for genetic algorithm.
Initialize the population of the genetic algorithm.

while a stopping criterion for the genetic algorithm is not satisfied.
  Assign fitness (using Algorithm 2) to each individual in the population;
  Select parents population with size of $pop \times r_s$;
  Do recombination operator based on the parents' population with rate r_c;
  Do mutation operator based on the parents' population with rate r_m;
  Generate offspring population based on the above three operators.
Endwhile

Algorithm 2. (second level) [26]

Step 1: Initialize a group of particles with random positions $x_i \in R^D$ and velocities $v_i \in R^D$ in the search space; Perform the next step until the pre-set requirements are satisfied.
Step 2: For each particle, compute fitness for each particle by using Eq. (11).
Step 3: Compare each particle' fitness with its$pbest_i$. If current value is better than $pbest_i$, then using current value instead of $pbest_i$ and update $p_i \in R^D$ with current location x_i; compare all of the particles' $pbest_i$ and find the best one assigned as and set its current location as $p_g \in R^D$.
Step 4: Update the particles' velocities and positions based on the following equation:

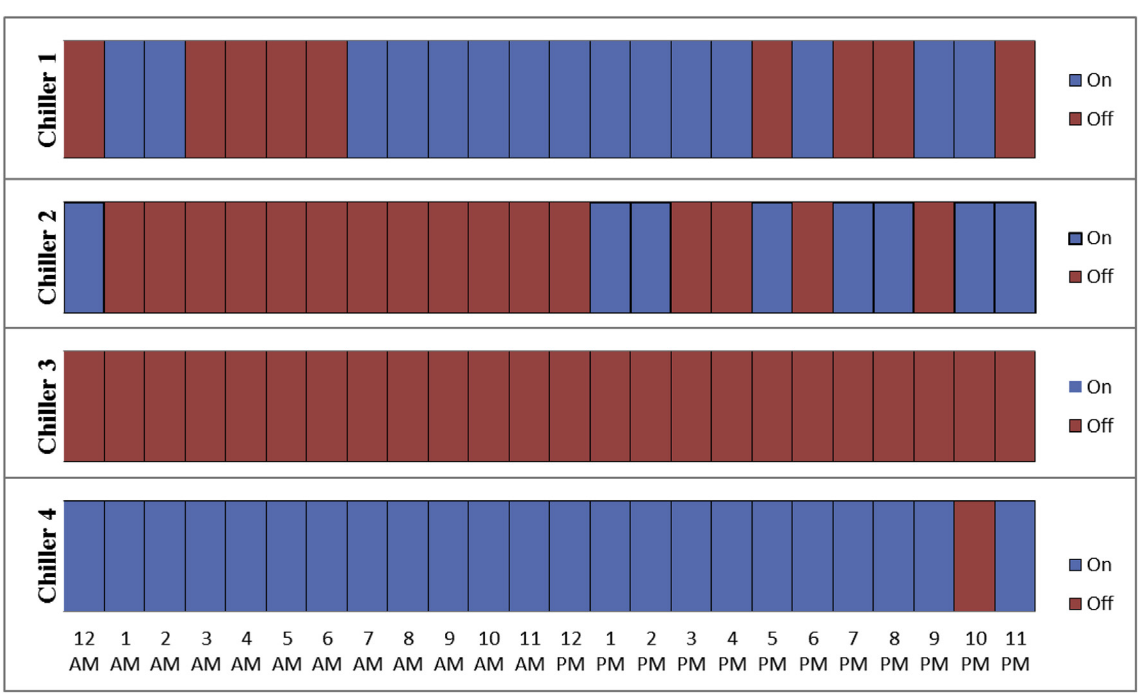

Fig. 13. The optimized strategy for controlling the four chillers on June 1, 2011.

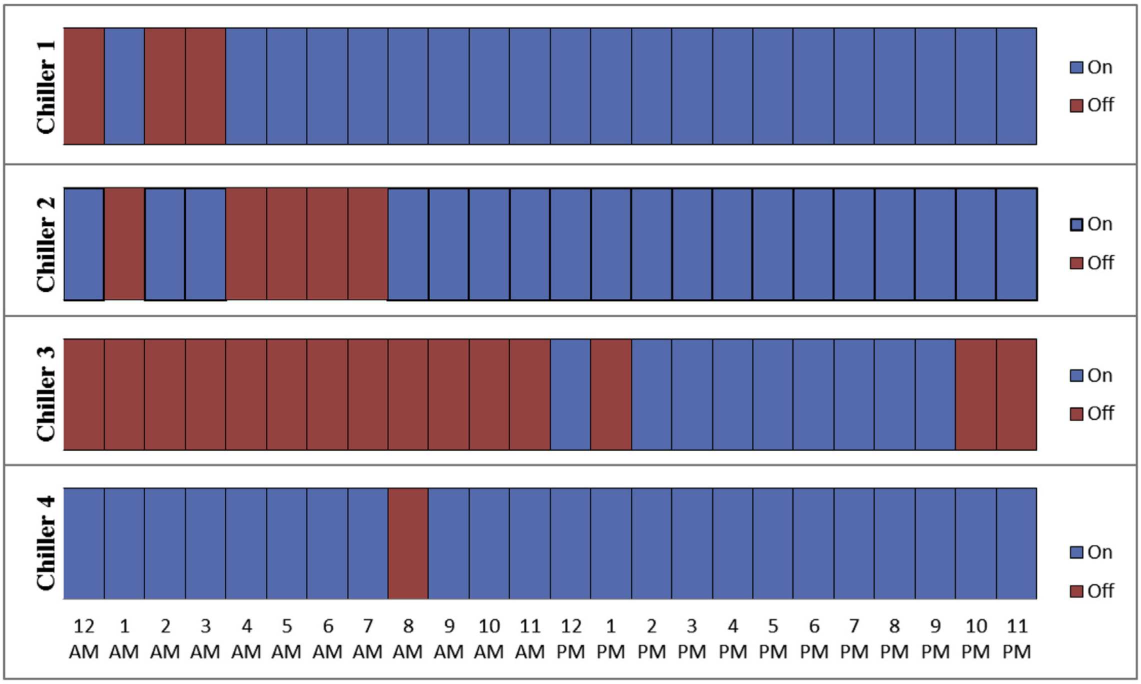

Fig. 14. The optimized strategy for controlling the four chillers on July 16, 2011.

$$v_i \leftarrow v_i + U(0,\varphi_1)\cdot(p_i - x_i) + U(0,\varphi_2)\cdot\left(p_g - x_i\right)$$
$$x_i \leftarrow x_i + v_i$$

Step 5: If the stop criterion is satisfied,p_g is the final solution and*gbest* is the final optimal fitness.

Note that $U(0,a)$ represents the uniform distribution in [0,a]; and should be within the range [$-v_{max}$,v_{max}].

4. Case study and results

The data in Table 5 illustrate the performance of the MLP models for prediction of the energy consumption of the four units. The accuracy of prediction models on test data sets is 98.16% for unit 1, 99.61% for unit 2, 96.55% for unit 3, and 97.85% for unit 4. Based on the high accuracy, the four prediction models are used to construct the optimization model discussed in the next section. Furthermore, Figs. 5–8 compare the predicted and observed values of the energy consumption of the four units on test data sets. As shown in

Table 6
The recommended cooling load (optimal chilled water flow) for four chillers on June 1, 2011.

Time	Recommended cooling for chiller 1 (Tons)	Recommended cooling for chiller 2 (Tons)	Recommended cooling for chiller 3 (Tons)	Recommended cooling for chiller 4 (Tons)
12:00 AM	0	2981	0	1770
1:00 AM	1588	0	0	2579
2:00 AM	1502	0	0	1292
3:00 AM	0	0	0	2521
4:00 AM	0	0	0	2360
5:00 AM	0	0	0	2243
6:00 AM	0	0	0	2324
7:00 AM	1500	0	0	1350
8:00 AM	1505	0	0	1731
9:00 AM	1509	0	0	1662
10:00 AM	1681	0	0	2575
11:00 AM	2651	0	0	2221
12:00 PM	2964	0	0	2580
1:00 PM	1501	2863	0	1290
2:00 PM	1578	2999	0	1329
3:00 PM	2773	0	0	2571
4:00 PM	2809	0	0	2570
5:00 PM	0	2817	0	2579
6:00 PM	2780	0	0	2575
7:00 PM	0	2914	0	2580
8:00 PM	0	2794	0	2578
9:00 PM	2643	0	0	2499
10:00 PM	2772	2981	0	0
11:00 PM	0	2932	0	2579

Note: the value zero indicates the corresponding chiller is turned off.

Table 7
The recommended cooling load (optimal chilled water flow) for four chillers on July 16, 2011.

Time	Recommended cooling for chiller 1 (Tons)	Recommended cooling for chiller 2 (Tons)	Recommended cooling for chiller 3 (Tons)	Recommended cooling for chiller 4 (Tons)
12:00 AM	0	2995	0	1921
1:00 AM	2762	0	0	2579
2:00 AM	0	2645	0	2579
3:00 AM	0	2624	0	2501
4:00 AM	2597	0	0	2457
5:00 AM	2603	0	0	2432
6:00 AM	2627	0	0	2522
7:00 AM	2997	0	0	2578
8:00 AM	2990	2997	0	0
9:00 AM	1589	2996	0	1593
10:00 AM	1540	2986	0	1674
11:00 AM	2642	2720	0	2352
12:00 PM	1505	2940	1487	2578
1:00 PM	2999	2999	0	2578
2:00 PM	1568	2937	1797	2564
3:00 PM	1501	2879	2555	2578
4:00 PM	2905	2972	1814	2570
5:00 PM	2995	2999	1719	2577
6:00 PM	2979	2985	1703	2550
7:00 PM	2954	2947	1674	2580
8:00 PM	2921	2985	1363	2558
9:00 PM	1529	2943	2535	2575
10:00 PM	1990	2968	0	2556
11:00 PM	2984	2997	0	1460

(Note: the value zero indicates the corresponding chiller is turned off).

Figs. 5–8, the predicted values of the energy consumption closely follow the observed values.

The data collected at two typical days are used to validate effectiveness of the proposed approach: one is a cool day (June 1, 2011) and another is a hot day (July 16, 2011). The cooling load demand for these two days is presented in Figs. 9,10. The corresponding observed energy consumption for the two days is shown in Figs. 11,12. In the optimization model, γ is set to 0.5. Q_i is refer to Table 1. The minimum and maximum entering water temperature is set to 75 °F (23.9 °C) and 85 °F (29.4 °C).

Applying the proposed optimization model to the two days, the optimized strategy for controlling the four chillers is shown in Figs. 13,14. The blue color (in web version)means the corresponding chiller is running during that time period while the red (in web

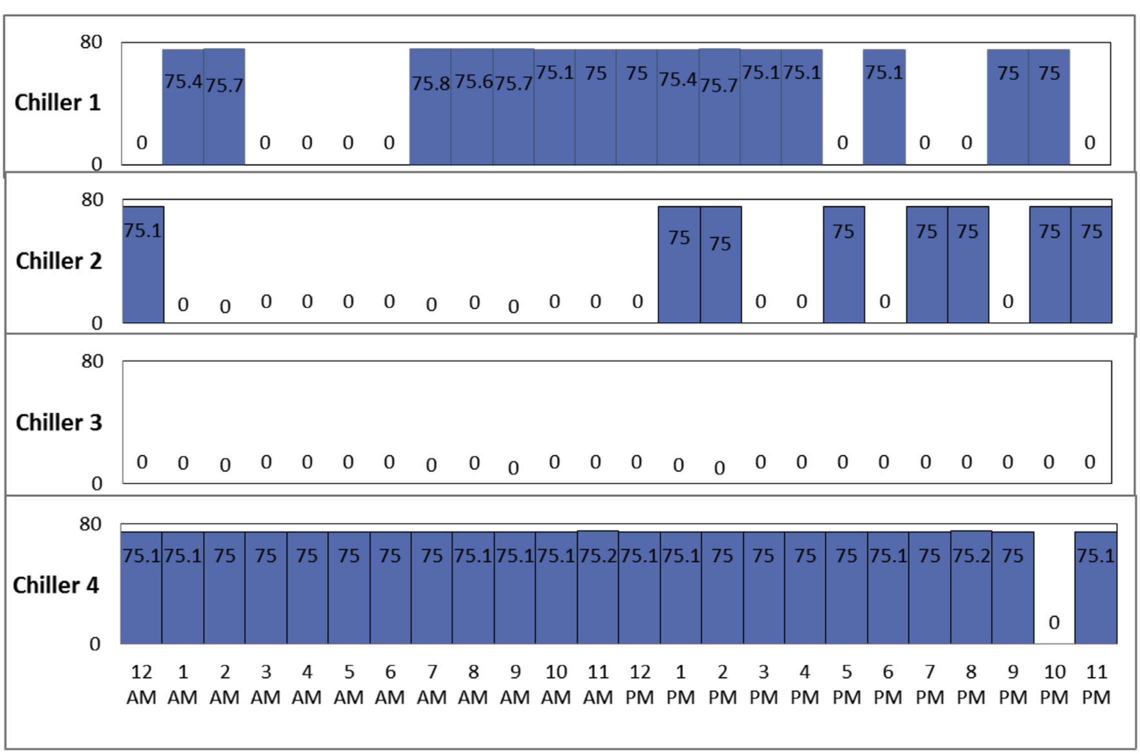

Fig. 15. The recommended entering water temperature (°F) for four condensers on June 1, 2011. (Note: the value zero means the corresponding chiller is turned off).

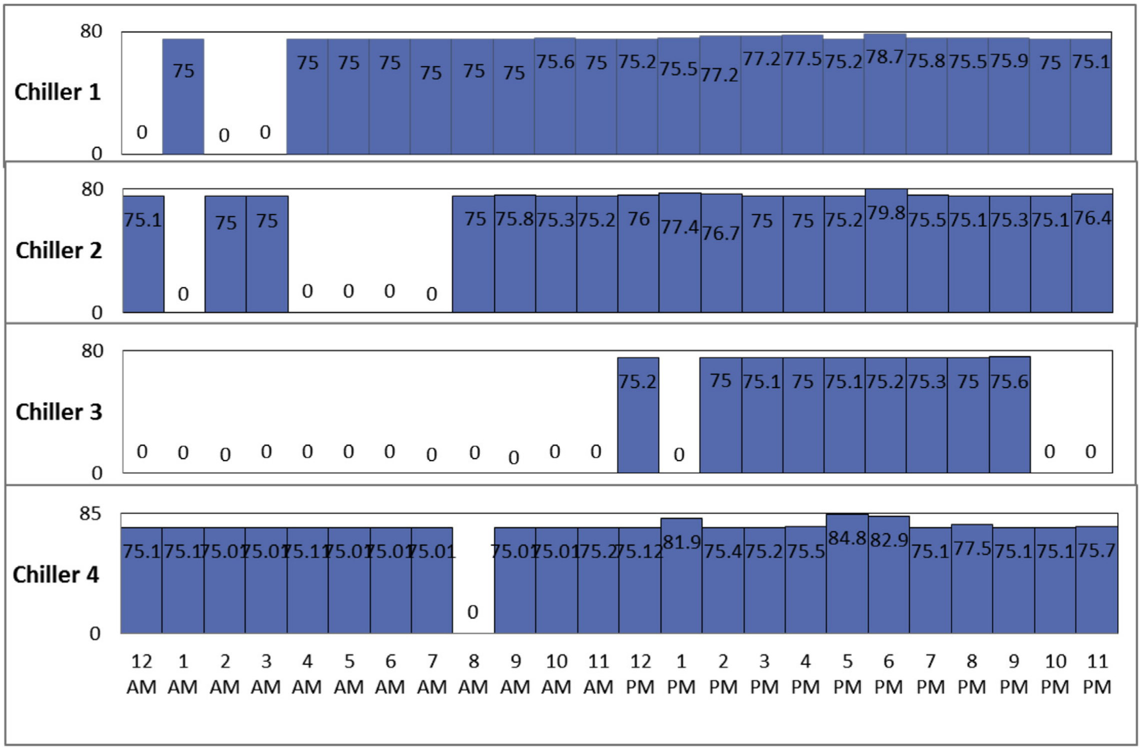

Fig. 16. The recommended entering water temperature (°F) for four condensers on July 16, 2011. (Note: the value zero indicates the corresponding chiller is turned off).

version) means the chiller is not running. The recommended chilled water flow for the four chillers and entering water temperature for the four condensers is illustrated in Tables 6 and 7 and Figs. 15,16. The value zero means the corresponding chiller at that time period is not running. Figs. 17,18 show the energy savings for the proposed approach for the two days compared to the observed values. Fig. 19shows the average observed and optimized power of the chiller plant of the two days. As illustrated as the number in Fig. 19, the proposed approach can achieve 14% energy saving on the selected two days.

In addition, the trend that charging the chilled water tank with low price and discharging with high price is not obvious from the computational results. The reason may be because of the additional operation cost to start one or more chillers to charge the tank. However, this is an interesting topic and the trend may be obvious for a large system which has more chillers, cooling towers and

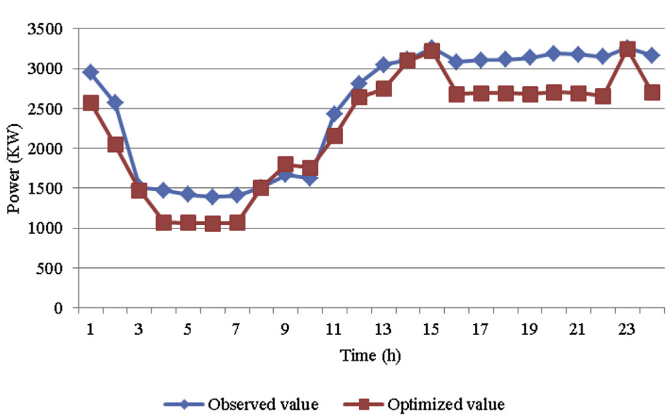

Fig. 17. The observed and optimized values of total energy of the chiller plant on June 1, 2011.

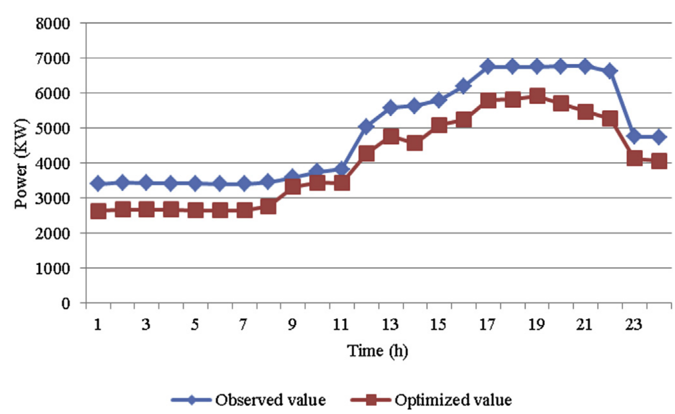

Fig. 18. The observed and optimized values of total energy of the chiller plant on July 16, 2011.

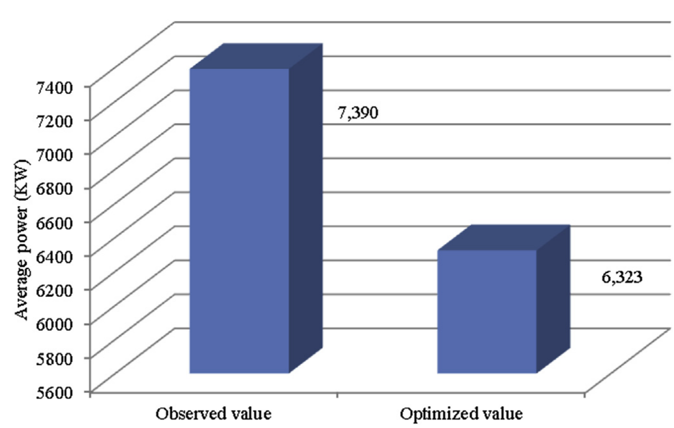

Fig. 19. The observed and optimized average power of the chiller plant of the two days.

chilled water tanks. It is worth to investigate this topic in the future research.

In terms of the computation time, the proposed two-level intelligent algorithm can complete the computation within 1 min for the two days simulation. As 1 h control of the chiller plant is feasible, therefore, it is applicable to employ the developed approach for online optimal control and operation of the chiller plant.

5. Conclusion

In this paper, the data-driven approach was employed to optimize the operation of a chiller plant in order to save energy consumption. The chiller plant included four chillers, four cooling towers of varying energy efficiency, and two chilled water storage tanks.

A model for scheduling a chilled water plant was derived with a data-driven approach. Multi-layer perceptron was used to build prediction models of energy usage and satisfied prediction accuracy was obtained. Due to the non-convexity and nonlinearity of the model, a two-level intelligent algorithm was proposed and used to solve the optimization problem. The model was tested on data from two different days. Computational results demonstrated a 14% energy saving by applying the proposed approach. By optimizing chiller on/off running status and controlling the entering cooling water temperature at optimal values, a significant energy saving can be achieved for a complete chiller plant.

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